

Ang Sun

Director of Research, Principal Scientist, inome

Outline

- The Slot Filling Challenge
- Overview of the NYU 2011 System
- Pattern Filler
- Distant Learning Filler

The Slot Filling Challenge

- Hand annotation performance
 - Precision: 70%
 - Recall: 54%
 - F-measure: 61%
- Top systems rarely exceed 30% F-measure

The Slot Filling Challenge

Query: <query id="SF114">

<query in= 5r112, <name>lim Parsons</name> <docid>eng-WL-11-174592-12943233</docid> <enttype>PER</enttype> <nodeid>Eo3oo13</nodeid> <ignore>per.date_of_birth, per:age, per:city_of_birth</ignore> </query>



DOC1000001:

After graduating from high school, Jim Parsons received an undergraduate degree from the University of Houston. He was prolific during this time, appearing in 17 plays in 3 years.

Response: SF114 per:schools_attended University of Houston

The Slot Filling Challenge

Entry level is pretty high

Jim Parsons was born and raised in Houston ... He attended Klein Oak High School in ...

- High performance name extraction
- High performance coreference resolution
-
- Extraction at large scale
 - 2011: 1.8 million documents
 - 2012: 3.7 million documents

The Slot Filling Challenge

- Documents have not gone through a careful selection process
 - Evaluation in a real world scenario
- Slot types are of different granularities
 - per:employee_of
 - org: top_members/employees
 -

The Slot Filling Challenge

Person		Organization org-alternate_names		
per:alternate_names	perstitle			
per:date_of_birth	per member_of	org political/religious_affiliation		
perage	per:employee_of	org.top_members/employees		
per.country_of_birth	per religion	org_number_of_employees/members		
per.stateorprovince_of_birth	perspouse	org members		
per:city_of_birth	perchildren	org.member_of		
per:origin	per parents	org:subsidiaries		
per:date_of_death	persiblings	org:parents		
per:country_of_death	per:other_family	org_founded_by		
per:stateorprovince_of_death	per:charges	org founded		
per:city_of_death		org:dissolved		
per:cause_of_death		org:country_of_headquarters		
per:countries_of_residence		org:stateorprovince_of_headquarters		
per:stateorprovinces_of_residence		org:city_of_headquarters		
per:cities_of_residence		org:shareholders		
per:schools_attended		org.website		

Overview of the NYU 2011 System





	patterns	
pattern set	patterns	slots
local patterns for person queries	title of org, org title, org's title, title	title, employee_of
	title in GPE, GPE title	origin, location_of_residence
	person, integer,	age

Pattern Filler

pattern set	patterns	slots		
local patterns for person queries	title of org, org title, org's title,	title, employee_of		
	title			
	title in GPE, GPE title	origin, location_of_residence		
	person, integer,	age		
local patterns for org queries	title of org, org title, org's title	top_members/employees		
	GPE's org, GPE-based org, org	location_of_headquarters		
	of GPE, org in GPE			
		subsidiaries / parent		
implicit organzation	title [where there is a unique org	employee_of [for person		
	mentioned in the current + prior	queries];		
	sentence]	top_members/employees [for		
		org queries]		
functional noun	F of X, X's F	family relations; org parents		
	where F is a functional noun	and subsidiaries		

Patter	n Filler
Hand cr	afted patterns
	th title and organization of Ford, Ford Freedent)
org-title-pattern	:= org-title-pattern1 / org-title-pattern2;
org-title-pattern1	:- (full-title):FullTitle "of" [constit cat-name pa-[head-ORGANIZATION]]:Org;
org-title-pattern2	:= [constit cat=name ps=[head=CRGANIZATION]]:Org "'s"7 (full-title):FullTitle;
full-title	:= title=mod* ((constit cat=n KSPtarget=true pa=[head)iss(titleOrOccupation)]]) (constit cat=title KSPtarget=true pa=[head)iss(titleOrOccupation)]]);
title-mod	:= [constit cat=n]:
<pre>// note value (ful when org-title-pat</pre>	
http://cs	s.nyu.edu/grishman/jet/jet.html













Pattern Filler

- Learned patterns (through bootstrapping)
 - Problem: semantic drift
 - Solutions:
 - Manually review top ranked patterns
 - Guide bootstrapping with pattern clusters





Distant Learning Filler

- **Distant Learning** (the general algorithm)
 - Map relations in knowledge bases to KBP slotsSearch corpora for sentences that contain name
 - Generate positive and negative training examples
 - Train classifiers using generated examples
 - Fill slots using trained classifiers

Distant Learning Filler

- Distant Learning
- Map 4.1M Freebase relation instances to 28 slots
- Given a pair of names <i,j> occurring together in a sentence in the KBP corpus, treat it as a
 - positive example if it is a Freebase relation instance
 negative example if <*i,j*> is not a Freebase instance but <*i,j*'> is an instance for some j'≠j.
- Train classifiers using MaxEnt
- Fill slots using trained classifiers, in parallel with other components of NYU system

Distant Learning Filler

Problems

pairs

- Problem 1: Class labels are noisy
 - Many False Positives because name pairs are often connected by non-relational contexts

	Microsoft	Bill Gat	es	
		Microsoft Bill Gat		
			Class Label	
		ire software	FALSE	
Bill Gates and Microsoft need to find some way to		POSITIVES		
	es has declared soft , Bill Gate	es has declared war on Microsoft's insecu soft , Bill Gates' relationship with India	es has declared war on Microsoft's insecure software nsoft , Bill Gates' relationship with India	

Distant Learning Filler

Problems

- Problem 1: Class labels are noisy
 - Many False Negatives because of incompleteness of current knowledge bases

Attribute of Person in Freebase	Incompleteness	Incompleteness(Attr.)
place_of_birth	0.792	1
places_lived	0.923	-
nationality	0.786	
parents	0.988	# Develop with out Atta
education	0.938	# Person without Attr.
employment_history	0.966	#Person

Distant Learning Filler

Problems

- Problem 2: Class distribution is extremely unbalanced
 - Treat as negative if <i,j> is NOT a Freebase relation instance Positive VS negative: 1:37
 - Treat as negative if
 - <*i*,*j*> is NOT a Freebase instance but <*i*,*j*'> is an instance for some **j**'≠**j** AND <*i*, *j*> is separated by no more than 12 tokens Positive VS negative: 1:13
 - Trained classifiers will have low recall, biased towards negative

Distant Learning Filler

Problems

- Problem 3: training ignores co-reference info Training relies on full name match between Freebase and text
- But partial names (Bill, Mr. Gates ...) occur often in text
- Use co-reference during training?
- Co-reference module itself might be inaccurate and adds noise to training
- But can it help during testing?

Distant Learning Filler

Solutions to Problems

- Problem 1: Class labels are noisy Refine class labels to reduce noise
- Problem 2: Class distribution is extremely unbalanced Undersample the majority classes
- Problem 3: training ignores co-reference info Incorporate coreference during testing

Distant Learning Filler--Class Label Refinement

- The refinement algorithm Represent a training instance by its dependency pattern, the shortest path connecting the two names in the dependency tree representation of the sentence
 - Estimate precision of the pattern $prec(p,c_i) = \frac{count(p,c_i)}{\sum count(p,c_j)}$
 - Precision of a pattern p for the class C is defined as the number of occurrences of p in the class C_i divided by the number of occurrences of \vec{p} in any of the classes C_j
 - Assign the instance the class that its dependency pattern is most 101 precise about

Distant Learning Filler--Class Label Refinement

- The refinement algorithm (cont)
 - Examples

Founded by	
William S. Paley	
Class	
PERSON: nployee_of	
ORG: Founded_by	

Distant Learning Filler--Undersampling the Majority Classes

Effort 1:

- multiple n-way instead of single n-way classification single n-way: an n-way classifier for all classes
 - Biased towards majority classes
- multiple n-way: an n-way classifier for each pair of name types
 - A classifier for PERSON and PERSON Another one for PERSON and ORGANIZATION
 -
- On average (10 runs on 2011 evaluation data) 180 fills for 8 slots single n-way:
 - multiple n-way: 240 fills for 15 slots

Distant Learning Filler--Undersampling the Majority Classes

Effort 2:

- Even with multiple n-way classification approach
- OTHER (not a defined KBP slot) is still the majority class for each such n-way classifier
- Downsize OTHER by randomly selecting a subset of them

Distant Learning Filler--Contribution of Coreference

- No use of co-reference during training
- Run Jet (NYU IE toolkit) to get co-referred names of the query
- Use these names when filling slots for the query
- Co-reference is beneficial to our official system
 - **P/R/F** of the distant filler itself
 - With co-reference: 36.4/11.4/17.4
 Without co-reference: 28.8/10.0/14.3









Overview of 2011 System

- Baseline: 2010 System (three basic components) 1) Document Retrieval
 - > Use Lucene to retrieve a maximum of 300 documents
 - > Query: the query name and some minor name variants 2) Answer Extraction
 - Begins with text analysis: POS tagging, chunking, name tagging, time expression tagging, and coreference
 - Coreference is used to fill alternate_names slots \geq
 - Other slots are filled using patterns (hand-coded and created semi-automatically using bootstrapping)
 - 3) Merging
 - Combines answers from different documents and passages, and from different answer extraction procedures

Overview of 2011 System

- Passage Retrieval (QA)
 - For each slot, a set of index terms is generated using distant supervision (using Freebase)
 - Terms are used to retrieve and rank passages for a specific slot
 - An answer is then selected based on name type and distance from the query name
 - Due to limitations of time, this procedure was only implemented for a few slots and was used as a fall-back strategy, if the other answer extraction components did not find any slot fill.

Overview of 2011 System

		score using only module score e						xcluding module	
module		recall pr		ecision F1		recall precision		F1	
distant sup		Rec	all	Precis	sion	F1	35.4	25.7	
distant sup	NYU1 (With QA)	25.	7	33.	6	29.1	34.5	26.2	
distant sup		26		177,550	÷		35.7	29.2	
alternate n	NYU2 (Without QA)	25.	2	35.	0	29.5	34.1	27.5	
local patter	Derference		13/1				33.4	23.8	
implicit org	it organization Performance			ce of NYU Systems		62.9	39.2	30.5	
functional nouns		0.5	1	23.8	1.0	25.1	35.3	29.3	
bootstrappe	tstrapped linear patterns			54.1	6.6	24.8	34.6	28.5	
1	d dependency patterns	1.8	-	36.2	3.4	25.0	35.2	29.2	